MANAGING FUNCTIONAL TRADE-OFFS IN THE MECHANICAL DESIGN OF INTEGRATED PRODUCTS USING MULTIOBJECTIVE MONOTONICITY ANALYSIS

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ABSTRACT

With the continuously increasing integration of (mechanical) products, the identification and management of trade-offs becomes a major task in product synthesis, with substantial effect on optimality and robustness of the final solution. At the same time, a rigorous and comprehensive study of trade-offs through mathematical design optimisation is often impractical in design, as efforts spent on modeling and optimizing are likely wasted if a chosen design is changed. Extending research on configuration redesign based on a multiobjective monotonicty analysis (MOMA), this paper presents three levels of evaluation for early design or redesign: (I) informal evaluation, (II) opportunistic evaluation, and (III) exhaustive evaluation. The chosen level depends on what knowledge the designer wants to gain, and the higher the level, the larger the analysis effort, the lesser the re-use of the information gained from the initial MOMA analysis respectively. The approach is illustrated using a novel drug delivery device, the Self-Orienting Millimeter-Scale Applicator (SOMA), for the oral delivery of protein compounds such as insulin.

Keywords: Embodiment design, Optimisation, Evaluation, Configuration design

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1 INTRODUCTION

Design in early product development involves synthesis of concepts at the functional level and of their embodiment in various physical realizations. The identification and management of trade-offs while ensuring optimality and robustness of the end product is a major task in this synthesis effort and an important area of design research and practice (Sigurdarson et al., 2019). As products become more tightly integrated, such a task becomes increasingly difficult. In mathematical design optimization, trade-offs are captured by the design objectives and constraints, and can be studied rigorously. At the same time, such optimization models rarely capture early design decisions, and, if they are, effort spent on modeling and optimizing is likely wasted if the chosen design configuration is changed. In this context, early design evaluation is mostly done through expert opinion, qualitative assessment, or basic quantitative analysis (Finger and Dixon, 1989), often supported by a wide range of heuristic frameworks for dependency analysis, e.g., Axiomatic Design (Suh, 1998), TRIZ (Altshüller, 1984), Quality-Function-Deployment (Hauser and Clausing, 1988), and Design Structure Matrices (Ulrich et al., 2020). These evaluations rely largely on the designer's pre-existing knowledge and do not account explicitly for the effect that constraints have upon dependencies among design objectives. In traditional systematic design, there is consequently no comprehensive method for a design engineer faced with a design trade-off to decide what might be the best decision: accept the trade-off, optimize the design with respect to this trade-off (e.g., select some Pareto point based on preference, or relax constraints), or make a design change to avoid the trade-off. As a result, the end product may not have the robustness and performance originally foreseen in early design, leading to iterations and delays (Sigurdarson et al., 2019).

This paper presents a specific strategy for identification and management of trade-offs while ensuring optimality and robustness of the end product, through successive evaluation of design configuration alternatives. The strategy is built upon the recently developed theory and methodology of Multiobjective Monotonicity Analysis (MOMA) (Sigurdarson et al., 2022b). Monotonicity Analysis (Papalambros and Wilde, 2017) was originally developed to allow monotonicity information to be leveraged to identify constraints that are *active* (i.e., affect the location of the optimum), allowing partial optimization and model reduction through back-substitution of active constraints. Importantly, this can help reveal relationships between design variables that are unique to the optimal design. In this spirit, the approach was extended in Sigurdarson et al. (2022b) to allow analysis and reduction of multiobjective problems. The *global* dependencies in the Pareto set that cause trade-offs are called *trade-off variables*, denoted $\overline{\underline{x}}$. Dependencies that do not cause tradeoffs are called *harmonious variables*, denoted $\overline{\overline{x}}$ or $\underline{\underline{x}}$. *Local dependencies* caused by constraints are called *Pareto constraints*, denoted $\mathbf{g}(\mathbf{x}, \tilde{\epsilon})$, because the activity of these constraints changes regionally or locally in the Pareto set. These activity changes are explored through *Pareto-optimal activity cases*. MOMA is a technique of dependency analysis that (1) is only preoccupied with identifying dependencies actually affecting the optimal design and (2) systematically accounts for the discontinuous dependencies caused by constraints.

The present paper extends previous research on the MOMA analysis (Sigurdarson et al., 2022b) and corresponding configuration redesign principles (Sigurdarson et al., 2022a) to address the challenge of early design evaluation. In this context, the paper's contribution is the introduction of three levels of evaluation for early design or redesign: (I) informal evaluation, (II) opportunistic evaluation, and (III) exhaustive evaluation. We demonstrate the evaluation process using the *SOMA* medical device that was also used in earlier MOMA implementations. For the sake of clarity, we delve directly into a summary description of the device and its associated optimization model, before then explaining all three evaluation levels in detail using this example case, followed by some final observations. In practice, the presented approach can be used if the design engineer has a sufficiently analytical bend and the time investment is warranted by the gains, particularly for products manufactured in large numbers or of high value and complexity.

2 THE SELF-ORIENTING MILLIMETER-SCALE APPLICATOR (SOMA) DEVICE

The **S**elf-**O**rienting **M**illimeter-Scale **A**pplicator (SOMA) is a medical device for oral delivery of protein compounds such as insulin. Such compounds cannot be administered orally as the gastric system breaks down large proteins and are hence administered using needle-based injection devices. First described

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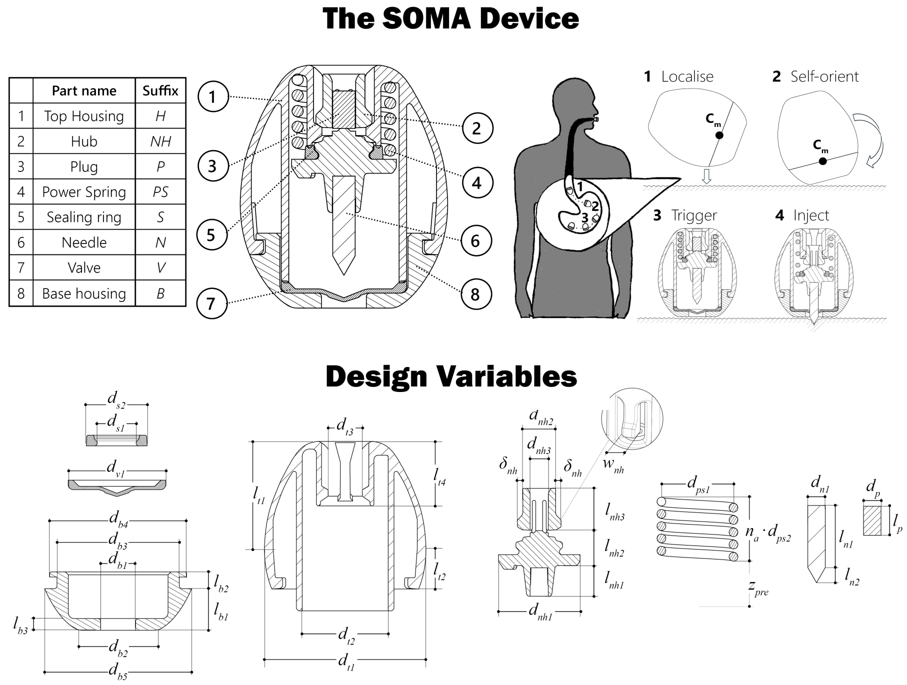

Figure 1. Original SOMA device and key design variables

by Abramson et al. (2019), SOMA was still in early development at the time of the present study. When swallowed, SOMA falls into the stomach, where it self-orients into a stable position on the lining of the stomach thanks to its shape and mass distribution, see Fig. 1. Once oriented, the compression spring 4 (top of Fig. 1) injects a solid *milipost* of insulin (6) or another Active Pharmaceutical Ingredient (API), penetrating into a deep enough tissue layer to reach capillaries where the milipost dissolves. The injection is triggered by a plug (3) which dissolves upon contact with liquid, allowing the compliant snap features on the hub (2) to pass through a ratchet interface on the top housing (1).

The device presents several trade-offs: It must reliably deliver a large enough amount of API to meet the dosage needs of patients without compromising the self-orientation performance or injection depth, while being small enough to be swallowed without discomfort. Hence, SOMA was used in Sigurdarson et al. (2022b) to demonstrate the use of Pareto set dependency analysis. The design problem is cast into a four-objective optimization model given below in upper-bound form (Papalambros and Wilde, 2017; Marler and Arora, 2004):

$$\min \quad f_1(\mathbf{x}) = -\frac{\sum_{p=1}^{p=8} m_p \cdot (C_p + Z_p)}{(l_{t1} + l_{t2} + l_{b1}) \cdot \sum_{p=1}^{p=8} m_p} \tag{1}$$

$$\text{subject to:} \quad c_1(\mathbf{x};\epsilon_1) = d_{t1} - \epsilon_1 \leq 0 \tag{2}$$

$$c_2(\mathbf{x};\epsilon_2) = \epsilon_2 - \rho \frac{\pi}{4} d_{n1}^2 \left(l_{n1} + \frac{1}{3} \cdot l_{n2} \right) \leq 0 \tag{3}$$

$$c_3(\mathbf{x};\epsilon_3) = \epsilon_3 - \sqrt{2\left(g + \frac{F_s}{m_{acc}}\right) z_{acc}} \leq 0 \tag{4}$$

$$\text{and } \mathbf{g}(\mathbf{x}) \leq 0, \mathbf{h}(\mathbf{x}) = 0, \mathbf{x}, \epsilon \in \mathbb{P} \tag{5}$$

where f_1 is a self-orientation objective maximising the normalized distance Z_{cm} between the top of the device and the system centre of mass C_m; m_p is the mass, C_p the centre of mass, and Z_p is the vertical position of each part of the device, respectively. Further, c_1 is the upper bound objective on size minimizing d_{t1}, as pill swallowability is proportional to its minor diameter (FDA-CDER, 2013); c_2 is the lower bound objective on API capacity maximizing the drug payload, and c_3 is the lower

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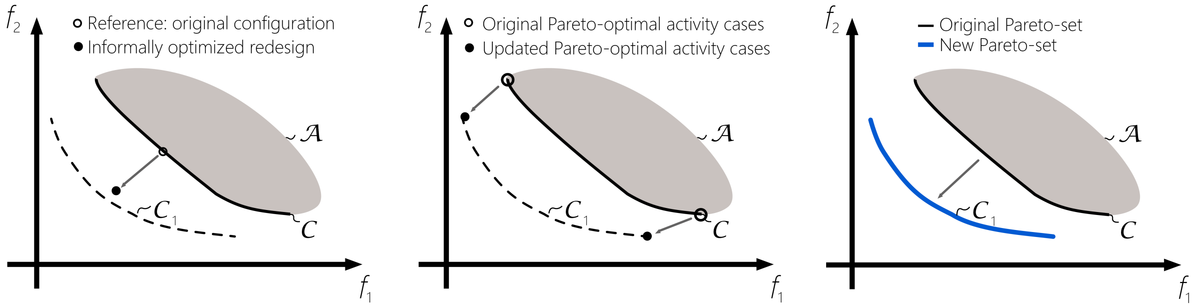

Figure 2. LEFT: Informal evaluation based on a single design point in the objective space reusing monotonicity and constraint activity knowledge from the preceding analysis. CENTER: Opportunistic evaluation seeks to identify potential vertices or bi-objective frontiers in the new Pareto set by updating constraint activities from the preceding design. RIGHT: Exhaustive evaluation by constructing a new optimization model to identify the entire Pareto set

bound objective on injection velocity maximising the velocity of impact between needle and tissue; F_s is a nonlinear expression for the accelerating force, m_{acc} the mass that is accelerated, z_{acc} the stroke between the initial position of the needle tip and the gastric tissue, and g is gravity. Constraints such as geometric fits between parts of the assembly, manufacturability, and structural load cases, are represented by $\mathbf{g}(\mathbf{x})$, while $\mathbf{h}(\mathbf{x})$ mostly accounts for the shape of the device. In Sigurdarson et al. (2022a) SOMA was used to illustrate the redesign methodology based on MOMA (Sigurdarson et al., 2022b) and identified improved configuration redesigns. In the present paper, we use SOMA to illustrate the design principles developed in Sigurdarson et al. (2023) for evaluating alternative design configurations without rebuilding a full optimization model.

3 METHODOLOGY

As noted in the introduction, early design evaluation is of essential importance in iterative design – in practice done through expert opinion, qualitative analysis, or basic quantitative analysis, such as single objective design optimization. While the MOMA-based trade-off analysis allows for systematic configuration redesign (Sigurdarson et al., 2022a), fully evaluating a redesign relative to the initial one would require comparison of the corresponding Pareto-sets with a new optimization model constructed for each individual configuration. When this comprehensive analysis is impractical, a complementary approach is to examine three levels of evaluation: *informal*, *opportunistic*, and *exhaustive*, which can be used during or after an iterative design improvement process, depending on what knowledge the designer wants to gain. The higher the level, the larger the analysis effort, and the lesser the re-use of the information gained from the application of MOMA to the initial design.

Here, the underlying rationale is that the knowledge gained during the initial configuration analysis is not lost just because the design is changed. So long as we have followed the analysis methodology (Sigurdarson et al., 2022b) and have applied the redesign principles described in Sigurdarson et al. (2022a) and Sigurdarson et al. (2023) systematically, we should know exactly how constraint activities and the relationships between the objectives and their trade-off variables have changed. We can leverage this knowledge to evaluate whether certain trade-offs have been successfully reduced or mitigated, or whether the Pareto frontier has shifted and the optimum of certain objectives improved. Figure 2 illustrates the different levels of evaluating how the initial Pareto set has been improved. The next sections describe them in more detail and demonstrate their application in a design context on the SOMA device.

4 LEVEL I: INFORMAL EVALUATION

Informal evaluation requires the least effort and relies on the reuse of information gained from MOMA of the initial design. Instead of comparing the entire Pareto sets, we therefore seek to gain insights by evaluating a redesign at single design points in the objective space. Its attributes are as follows.

Level of Abstraction: Evaluation of updated objective functions for a redesign at a single design point in the objective space and comparison with the Pareto set of the initial design.

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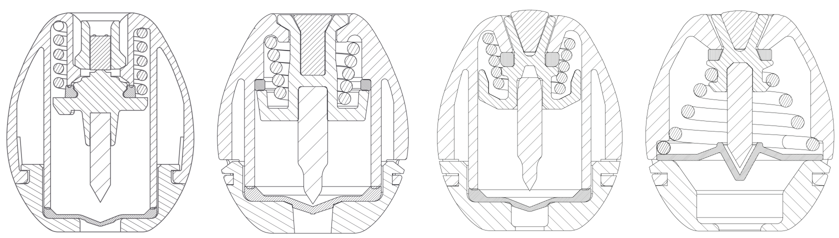
Re-used Knowledge: Monotonicity and constraint activity information from the original analysis, combined with the elements of the optimization model that are unaffected by design changes.
Uses: Assessment of whether the configuration redesign principles have been successfully applied. Simple comparisons with alternative redesigns, assuming that approximate knowledge of the relative importance of the objectives exists.
Limitations: If there are new or changed constraint functions resulting in unforeseen or changed constraint activity, then the evaluated design may be infeasible unless it is accounted for during analysis. Furthermore, the informal nature of the proportional design of the new configuration(s) means that we might be comparing the optima of the original design with a design that is far from the new optimal set.
Process Steps: An informal evaluation process might involve (i) updating the objective functions to reflect design changes; (ii) modeling the design in CAD, using monotonicity information to informally optimize it; (iii) using the updated objective functions or CAD/CAE to evaluate how well the informally optimized design performs; and (iv) comparing current design with the initial or preceding one.

In practice, we might be able to informally optimize the system while dimensioning it in a CAD environment, a task which would take far less time than constructing a completely updated optimization model. One might also utilise CAE tools to evaluate specific objectives and constraints affected by the design changes. The new design could then either be compared with the original entire Pareto set or with a reference point in it. If no trade-off variables or new constraints have been introduced by the design changes, this might indicate how far the new Pareto set has been moved or reshaped. In ongoing development projects, one might often have an already dimensioned version of the original design in CAD, which can be used as a reference for comparison, as it will likely reflect the relative weighting of the objectives. As seen in the SOMA case, the reference design used to build the optimization model was actually found to be quite close to being Pareto optimal already Sigurdarson et al. (2022b). This knowledge might allow comparisons with other configuration redesigns, help decide whether the construction and solution of a whole optimization model is worthwhile, or substantiate that investment in prototyping and testing the redesigned configuration is worthwhile.

4.1 Level I example: CAD-based evaluation of SOMA redesigns

Three out of the four design objectives in SOMA can be simply evaluated in a CAD environment, so that redesign iterations were modelled and dimensioned in CAD (PTC Creo Parametric 4.0). The three new configurations shown in Fig. 3 were drawn and dimensioned using monotonicity and constraint activity information from the original model. Specifically, they were aiming at reducing the outer diameter, increasing the spring force, increasing the acceleration stroke (z_{acc}), and reducing the height of the steel base (ultimately determined by l_{t2}). From our knowledge of the relevant constraints and how they are affected by the design changes, it is straightforward to model seemingly feasible proportional designs of new configurations. The same parameter values were used in CAD as in the original optimization model. Meanwhile, the API mass was roughly kept comparable to that of the original SOMA design.



	SOMA:	Flipped Seal	Wedge Trigger	Flipped Actuator
Z_{CM}	-0.65 h	-0.67 h	-0.68 h	-0.69 h
Ø	11.12 mm	8.37 mm	9.05 mm	9.05 mm
M_{API}	3.15 mg	3.4 mg	3.4 mg	3.4 mg
V_{IMP}	26.3 m/s	33.7 m/s	37.5 m/s	39.4 m/s

Figure 3. A comparison of the SOMA device with realizations of three of the redesign iterations.

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Different approaches were used to evaluate how well these dimensioned realisations of the redesigned configurations meet the design objectives. The centre of mass was evaluated using a mass distribution evaluation routine in Creo, which takes a matter of seconds compared to the time-intensive effort in building continuous volumetric expressions for all changed components and applying these to evaluate the system centre of mass for each redesign. The device diameter and needle mass were also simply measured from the CAD model. Finally, the impact velocity was evaluated by updating the objective function to reflect the changed spring design and measuring part masses and acceleration stroke (z_{acc}) in the CAD model. To ensure feasibility, the von Mises stress in each spring and the interface stress in the trigger was evaluated. The three new designs and the evaluation results are shown in Fig. 3 along with the original SOMA design as a reference.
As can be seen, each of the informally optimized redesigns exhibits improved performance w.r.t. every single objective. This indicates that the trade-offs between the design objectives have indeed been reduced. All three redesigns dominate a substantial portion of the original Pareto set identified in Sigurdarson et al. (2022b), given the substantial simultaneous reduction of diameter and increase in impact velocity. All of them have an impact velocity that lies beyond the maximum seen in the original Pareto set (28.3 m/s). Further, all are below a diameter of 9.9 mm, which is the largest standard oral capsule size today, making for a more swallowable device. Hence, based on this simple evaluation, we know that all three redesigned configurations at least dominate a region of the original Pareto set.

5 LEVEL II: OPPORTUNISTIC EVALUATION

Assuming that the Pareto constraints are still active, we can use them to evaluate how the shape of the Pareto set, or certain vertices and regions of the set, have changed due to the configuration redesign. The attributes of Level II evaluation are as follows.

Level of Abstraction: Evaluation of how important Pareto optimal activity cases are affected by the design changes. This may reveal regional or global changes to the Pareto-set.
Re-used Knowledge: Monotonicity and constraint activity information from the original analysis, results of ϵMA, and what configuration redesign principles were applied where.
Uses: An assessment of whether the Design Improvement Criterion is fulfilled locally or regionally in the new Pareto set, i.e., whether the achievable performance is at least equal or better than that of the previous design w.r.t. all criteria Sigurdarson et al. (2022a). This allows evaluation of whether the trade-offs between certain objectives have been reduced, or single objective optima improved.
Limitations: If there are new or changed constraint functions, resulting in unforeseen constraint activity, then the design points involved in the updated Pareto-optimal activity cases may be inactive or exist outside the attainable set.
Process Steps: An opportunistic evaluation process might involve: (i) Updating MOMA to reflect any changes in constraint activity that result from the design changes; (ii) redoing the model reductions in order to update the constraint activity cases identified in the previous application of ϵMA, to reflect the design changes; (iii) comparing the resulting trade-off expressions or Pareto optimal vertices with those studied in the preceding design.

Again, we can re-use much of the information gained in MOMA and ϵMA to explore how the extrema of the new Pareto set have been affected by design changes. If it is possible to reduce the original optimization model to a point where explicit expressions describing the relationships between the objectives at the optimum are revealed, opportunistic evaluation allows comparison of Pareto frontiers between specific objective pairs. If not, then one could evaluate how some of the single-objective optima have changed as a result of configuration redesign.

5.1 Level II example: Re-use of trade-off and activity knowledge to evaluate redesigns

In the analysis of the original SOMA device, it was found that a set of geometric constraints ensuring that the parts fit together radially, i.e., the plug into the hub, the hub into the top housing, etc., limited the achievable combination of outer diameter and impact velocity. Looking at the Pareto Optimal activity cases, these constraints reveal some of the effects of the changes made to the configuration design.

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Before the model was reduced, the radial fit constraint describing the fit between the top and base housings as a function of the location of the split line, had the form:

$$g_1(d_{t1}^-, l_{t1}^-, l_{t2}^+, d_{b5}^+) = d_{b5} - \sqrt{\frac{2(l_{t1} - l_{t2})d_{t1}^2}{l_{t1}} - \frac{(l_{t1} - l_{t2})^2 d_{t1}^2}{l_{t1}^2}} \leq 0, \tag{6}$$

where the superscripts $^-$ and $^+$ indicate decreasing and increasing monotonicity respectively. The application of MOMA revealed that diameter of the base at the housing split d_{b5} is defined at the optimum by a set of active constraints allowing the partial minimization of the model using the corresponding formulation $d_{b5}^* = d_{t2} + 2R_{ov} + 6R_{wt} + 4R_{cl}$. Essentially, the diameter is defined by the inner diameter of the guiding cylinder (d_{t2}), the thickness of the existing walls, the corresponding assembly clearances, and the overlap in the housing assembly snap,

$$g_1(d_{t1}^-, l_{t2}^+, d_{t2}^+) = d_{t2} + 6R_{wt} + 4R_{cl} + 2R_{ov} - \sqrt{\frac{2(l_{t1} - l_{t2})d_{t1}^2}{l_{t1}} - \frac{(l_{t1} - l_{t2})^2 d_{t1}^2}{l_{t1}^2}} \leq 0. \tag{7}$$

Correspondingly, the guiding cylinder is defined at the optimum by the spring needing to fit inside it ($d_{t2}^* = d_{ps1} + d_{ps2} + 2R_{cl}$), while the coiling diameter of the spring is defined by the spring needing to fit around the trigger ($d_{ps1}^* = d_{ps2} + 2\delta_{nh} + d_p + 4R_{wt} + 6R_{cl}$). Combined with the diameter objective back-substituted, this yields the reduced expression:

$$\begin{aligned} g_1(\tilde{\epsilon_1}^-, l_{t2}^+, d_{ps2}^+, d_p^+, \delta_{nh}^+) &= 2d_{ps2} + 2\delta_{nh} + d_p + 10R_{wt} + 12R_{cl} \\ &+2R_{ov} - \sqrt{\frac{2(C_T\tilde{\epsilon_1} - l_{t2})\tilde{\epsilon_1}}{C_T} - \frac{(C_T\tilde{\epsilon_1} - l_{t2})^2}{C_T^2}} \leq 0. \end{aligned} \tag{8}$$

Further reductions depend on which constraint is active, with three possible Pareto-optimal activity cases, one of which revealed the single objective optimum of the device size ($\underline{\tilde{\epsilon_1}}$):

$$\overline{d_{ps2}} = 0.5(\tilde{\epsilon_1} - 4\delta_{nh}(d_{ps2}^+; \sigma_c, \sigma_y) - 6.9\text{mm}) \tag{9}$$

$$\wedge \underline{\tilde{\epsilon_1}}^* = 2d_{ps2} + d_p + 2\delta_{nh} + 7\text{mm} \tag{10}$$

$$\wedge \overline{l_{t2}} = l_{t2}(\tilde{\epsilon_1}^+, d_p^-, d_{ps2}^-, \delta_{nh}^-) \tag{11}$$

Comparing the *Flipped seal* configuration (shown in Fig. 3) - with the original design, we have introduced several changes which affect these Pareto-optimal activity cases. By changing the design of the housing snap to a hole in the top housing, we have eliminated $2R_{ov}$ from Eq. (7). The inner diameter of the guiding cylinder has changed to $d_{t2}^* = 2R_{ov} + 2R_{cl} + d_{ps1,1} + d_{ps2}$, where $2R_{ov}$ is contributed by the radial thickness of the sealing o-ring, and $d_{ps1,1}$ is the major coiling diameter of the conical spring. As the trigger arms need to fit through the top of the spring without collision, the major coiling diameter is determined by $d_{ps1,1}^* = 2\delta_{nh} + d_{ps2} + d_p + 2R_{wt} + 4R_{cl}$. Due to the redesign of the trigger, two wall thickness contributions (R_{wt}) and two clearance contributions R_{cl} have been eliminated from the greatest lower bound (glb) of the coiling diameter, compared to the glb of the original spring coil. Inserting these changes into Eq. (7) yields:

$$\begin{aligned} g_1(d_{t1}^-, l_{t2}^+, d_{t2}^+) &= 2d_{ps2} + 2\delta_{nh} + d_p + 8R_{wt} + 10R_{cl} + 2R_{ov} \\ &- \sqrt{\frac{2(l_{t1} - l_{t2})d_{t1}^2}{l_{t1}} - \frac{(l_{t1} - l_{t2})^2 d_{t1}^2}{l_{t1}^2}} \leq 0 \end{aligned} \tag{12}$$

Using this to update the Pareto optimal activity cases yields:

$$\overline{d_{ps2}} = 0.5(\tilde{\epsilon_1} - 4\delta_{nh}(d_{ps2}^+; \sigma_c, \sigma_y) - 5.7\text{mm}) \tag{13}$$

$$\wedge \underline{\tilde{\epsilon_1}}^* = 2d_{ps2} + d_p + 2\delta_{nh} + 5.8\text{mm} \tag{14}$$

$$\wedge \overline{l_{t2}} = l_{t2}(\tilde{\epsilon_1}^+, d_p^-, d_{ps2}^-, \delta_{nh}^-) \tag{15}$$

As can be seen from these expressions, the trade-off between velocity and size has been reduced drastically via. the relationship between $\overline{d_{ps2}}$ and $\tilde{\epsilon_1}$, as has the single objective minimum $\underline{\tilde{\epsilon_1}}$. Inserting the

global minimum feasible values of the remaining variables into the above expression, we find that the single objective minimum is $\underline{\tilde{\epsilon_1}}^* = 7.7\text{mm}$. Note that while $\overline{l_{t2}}$ remains unchanged w.r.t. which variables it depends on, the reduction in parametric contributions still applies.
We cannot directly calculate the single objective optimum of the impact velocity without calculating the system masses. That said, the minor coiling diameter $d_{ps1,2}$ is defined by the trigger arms needing to fit through the whole spring during assembly, meaning $d^*_{ps1,2} = d_{ps2} + 2\delta_{nh} + 2R_{wt} + 3R_{cl}$. Combined with the change to $\overline{d_{ps2}}$ and that $\underline{d_{ps1,1}}$ is smaller than the minimum coiling diameter in the original design, it clear that this redesign achieves a much stiffer and more volumetrically efficient spring coil than the original. Given this information, and given that we have identified the optimal size, we can conclude with a relatively high degree of confidence that the Pareto frontier between size and velocity has been improved substantially.
Applying the same approach to the *Flipped Actuator* reveals even more drastic changes. As the spring now needs fit around the needle (d_n), the activity cases for wire diameter and device size changes to:

$$\overline{d_{ps2}} = \frac{\tilde{\epsilon_1} - d_n - 4R_{wt} - 4R_{cl}}{2n_a} - R_{cl} \tag{16}$$

$$\wedge \underline{\tilde{\epsilon_1}}^* = d_n + 2n_a(d_{ps2} + R_{cl}) + 2.2\text{mm} \tag{17}$$

In order to calculate a minimum size, we would hence have to update the yield stress constraint for the spring and the axial fit constraints. This would also give a basic idea of how much spring force and acceleration stroke can be achieved for a given device size. For the sake of brevity, we will not include this evaluation here. This does, however, serve to show that we can actually learn a lot about the relationships that exist at the optimum of the new design without building an entire new optimization model, thanks to the outputs of MOMA and the redesign methods put forward in Sigurdarson et al. (2022a). We could also, in principle, leverage this knowledge to attempt to identify further design improvements.

6 LEVEL III: EXHAUSTIVE EVALUATION

If we want certainty that a redesign represents an improvement, one must construct an updated multi-objective optimization model describing the redesign and identifying its Pareto set. Luckily, this does not necessarily mean that one needs to build an entirely new model. The attributes of the exhaustive evaluation are as follows.
Level of Abstraction: Comparing whole Pareto-sets using a rebuilt optimization model describing the redesign(s) in question.
Re-used Knowledge: Constraint and objective functions that are unaffected by the design changes.
Uses: Evaluating whether a configuration redesign is *better* than the original, irrespective of the relative importance of the different design objectives. Hence, this can be used for redesign selection and/or for an additional round of MOMA+ϵMA and subsequent configuration design improvement process.
Limitations: If the fidelity of the new optimization model(s) is not the same as the fidelity of the original optimization model - e.g. due to incomplete data or a lack of design maturity - the Pareto-sets are not necessarily comparable. Furthermore, constraints that do not exist in the original design might get overlooked due to a lack of knowledge surrounding the new, less matured configuration design.
Process Steps: The exhaustive evaluation process involves: (i) Constructing a new optimization model to account for the configuration design changes or updating the existing one; (ii) verifying the well-boundedness of said model and checking the validity of the expressions used: (iii) solving numerically across a broader range of ϵ values than the original model to explore the new Pareto set; and (iv) identifying the meta Pareto-set and evaluating whether the redesign fulfils the design improvement criterion.

Application of some redesign strategies will likely require an optimization model more distant from the original. If we have relaxed only the constraints on harmonious variables, it would be sufficient to rebuild the affected constraint functions. Manipulating trade-off variables will always result in changed objective functions. The amount of re-use depends entirely on the types of objective and constraint functions involved. For characteristics such as mass distribution (as in the ensuing case), even the smallest configuration design change can have a drastic impact from a mathematical perspective.

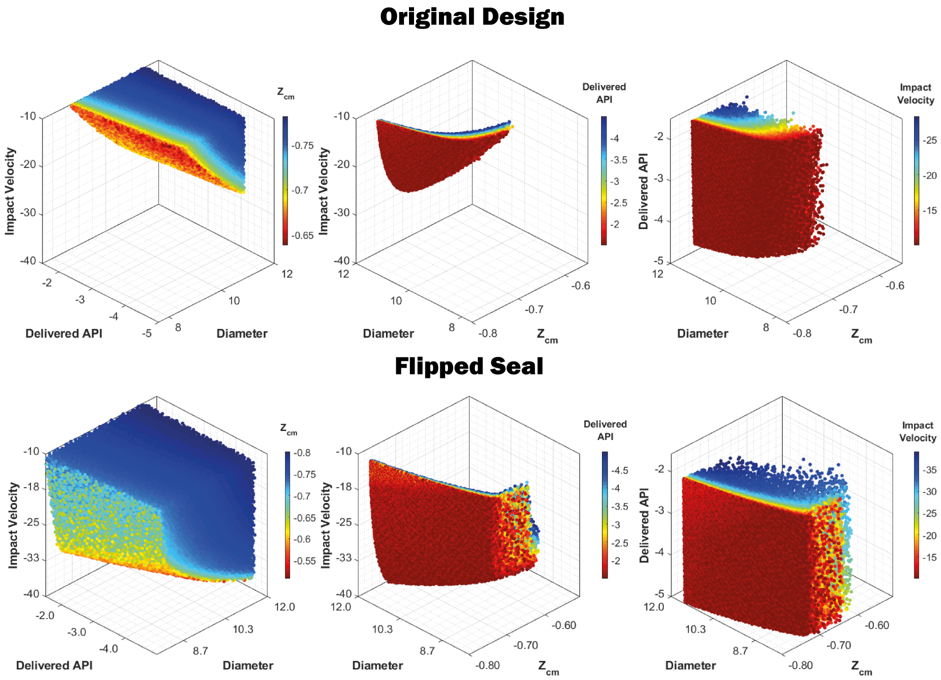

Figure 4. Different projections of the the 4D Pareto-set for the SOMA design and the Flipped Seal configuration. The improvement is seen in how the new Pareto set is much closer to origin.

6.1 Level III example: Exhaustive evaluation of a SOMA redesign

An exhaustive evaluation of every single redesign iteration is usually more time-consuming than what is worthwhile in development practice. For the SOMA case, this especially applies for the amount of effort involved in deriving an accurate analytical expression for the mass distribution of the system.

While this underlines the importance of the preceding levels of evaluation, we may still need assurance that the configuration redesign is a true improvement. To demonstrate the validity of the systematic redesign procedure, we can exhaustively evaluate a single redesign iteration and compare it against the original, as also described in Sigurdarson et al. (2022a). The Flipped Seal configuration from Fig. 3 is selected for such a comparison for three reasons: (a) it allowed substantial re-use of expressions from the original optimization model; (ii) it still involves influential configuration design changes, thereby demonstrating how large an influence trade-off variables, Pareto constraints, and restrictively bounded harmonious variables can have upon the achievable performance: (iii) the company developing the SOMA device was most interested in this evaluation, as bigger changes to the configuration design might introduce higher uncertainty. The flipped seal exhibited no changes in working principles and resembled the original design.

A new optimization model was built containing new constraint functions to reflect the new part fits, new and updated expressions for mass distribution to reflect the changes in geometry, and changes in the spring equations to reflect the conical shape. The model structure, governing equations, and level of detail remained unchanged. Of particular note are the radial fit constraints describing how the trigger arms fit within the spring. This snap feature only needs to avoid collision with the spring during the injection. As it can flex inward during assembly, the diameter of the lower portion of the spring coil is only constrained by the outer diameter of the trigger arms without the plug, which allows for a more conical shape than one might otherwise surmise.

The model was run with 200,000 iterations, with $\epsilon_{\mathbf{L}} = [7\text{mm}; 1.5\text{mg}; 10\text{m/s}]$ and $\epsilon_{\mathbf{U}} = [11.5\text{mm}; 5\text{mg}; 45\text{m/s}]$. The results in Fig. 4 show the new Pareto set lying beyond the original one. For the union of the Pareto sets, $\mathcal{C}_{\mathcal{U}} = \mathcal{C}_0 \cup \mathcal{C}_2$ the meta Pareto-set was found to only consist of solutions from the 2$^{\text{nd}}$ redesign, i.e., $\check{\mathcal{C}} = \mathcal{C}_2$, and the single-objective optima of self-orientation has been improved by 2.63%, the size by 12.41 %, API payload by 11.11%, and velocity by 37.68%. We can thus conclude that the redesign is, in fact, a design improvement. For the subsequent redesigns, it is clear that the achievable combination of impact velocity and self-orientation is improved even further,

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as the design changes are aimed at increasing the load-bearing area in the trigger system and shifting the centre of mass downward while increasing the acceleration stroke. The informal and opportunistic evaluations also support this.

7 CONCLUSION

Building on the theory of previous work, we derived a methodology that is generally applicable in an opportunistic way, namely, when configuration design changes justify the additional analysis effort for quantitatively evaluating and comparing redesigns. The SOMA design is a case where substantial insights on the properties of the optimal set can be gained for the redesigns, even with limited analysis effort. Such insights might be used to identify and select the most promising configuration for further work, or be used to steer additional redesign efforts, following the analysis and redesign methodology developed in Sigurdarson et al. (2022b) and Sigurdarson et al. (2022a).

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